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Citation for final published version:

Monroy, Claire, Meyer, Marlene, Schroer, Lisanne, Gerson, Sarah ORCID: <https://orcid.org/0000-0001-8710-1178> and Hunnius, Sabine 2019. The infant motor system predicts actions based on visual statistical learning. *NeuroImage* 185 , pp. 947-954. 10.1016/j.neuroimage.2017.12.016 file

Publishers page: <https://doi.org/10.1016/j.neuroimage.2017.12.016>
<<https://doi.org/10.1016/j.neuroimage.2017.12.016>>

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The infant motor system predicts actions based on visual statistical learning

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This work was supported by an Initial Training Network (ITN) of the People Marie Curie Actions—Seventh Research Programme (FP7) of the European Union (FP7ITN2011-289404).

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Abstract

Motor theories of action prediction propose that our motor system combines prior knowledge with incoming sensory input to predict other people's actions. This prior knowledge can be acquired through observational experience, with statistical learning being one candidate mechanism. But can knowledge learned through observation alone transfer into predictions generated in the motor system? To examine this question, we first trained infants at home with videos of an unfamiliar action sequence featuring statistical regularities. At test, motor activity was measured using EEG and compared during perceptually identical time windows within the sequence that preceded actions which were either predictable (deterministic) or not predictable (random). Findings revealed increased motor activity preceding the deterministic but not the random actions, providing the first evidence that the infant motor system can use knowledge from statistical learning to predict upcoming actions. As such, these results support theories in which the motor system underlies action prediction.

Keywords: mu rhythm, EEG, infants, statistical learning, action prediction

Visual statistical learning leads to predictive motor activation in the infant brain

1.0 Introduction

According to motor theories of action observation, we predict the actions of other people by means of our own motor system (Flanagan & Johansson, 2003; Kilner, 2011; Rizzolatti & Craighero, 2004). When we perceive someone reach for a coffee mug at the breakfast table, we already anticipate they will next bring the mug to their mouth. This anticipation takes place in cortical pre-motor regions that are active both when performing and observing actions or their effects (Kilner et al., 2004; Paulus, et al., 2013). Motor predictions of observed actions are thought to underlie adaptive social interaction (Sebanz & Knoblich, 2009) and inferring the goals and mental states of others (Becchio et al., 2012; Gallese & Goldman, 1998; Ondobaka et al., 2015).

However, a challenge for the motor system is that perceptually similar actions can result in very different outcomes. As a consequence, predictions cannot always be made on the basis of the current ongoing action alone (Jacob & Jeannerod, 2005). Motor accounts of action prediction have been criticized for failing to explain how action predictions can be generated for cases in which the observed motor act itself does not contain enough information to make an accurate prediction (Kilner et al., 2007). To solve this ambiguity problem, recent probabilistic accounts have emerged that are largely based on principles of predictive coding (Friston, 2003, 2005). The core idea in this approach is that the motor system combines prior knowledge with incoming sensory input to determine the most likely action outcome (Kilner et al., 2007; Ondobaka et al., 2015; Wolpert et al., 2003). If the person reaching for her coffee mug is standing next to the sink

with a sponge in hand, this will elicit a different motor prediction based on the observer's world knowledge that her intention is most likely to wash the mug. Crucially, these accounts rest on the assumption that this prior knowledge is 'fed' into the motor system and allows it to generate an accurate prediction based on the current action context.

Predictive processing accounts provide a solution for the ambiguity problem, yet raise a new challenge: how does new action knowledge—acquired from perceptual information—become encoded in the motor system? Observational experiences are one important route to prior knowledge, particularly during development (Hunnius & Bekkering, 2014). An infant may, for instance, observe a parent reach for a peanut butter jar, which could be followed by many possible outcomes. However, if the majority of the time their parent then removes the lid, scoops peanut butter from the jar and reaches for a slice of bread, after multiple observations, the infant can predict what is most likely to occur next when their parent first grasps the jar. In this example, the statistical regularities between action steps provide information that the infant can learn through observational experiences.

This ability is referred to as statistical learning (SL), a powerful mechanism that explains how humans can acquire knowledge of the environment through observation (Perruchet & Pacton, 2006). SL skills broadly refer to the ability to detect regularities in continuous sensory input, and have been demonstrated empirically across sensory modalities and across the lifespan (Conway & Christiansen, 2005; Fiser & Aslin, 2005; Kirkham et al., 2007; Saffran et al., 1996; Slone & Johnson, 2015). A few recent studies have shown that both infants and adults are also sensitive to the statistical regularities in continuous human actions (Ahlheim et al., 2014; Baldwin et al., 2008; Monroy et al., 2017; Stahl et al., 2014). For instance, Baldwin and colleagues (2008) investigated whether observers can parse action streams according to the

93 transitional probabilities between action steps. In their experiment, adult participants observed an
94 action stream made of 3-step action elements presented continuously, such as ‘pour-poke-clink’
95 or ‘peek-clink-rattle’. Participants were next shown ‘action’ sequences (the original 3-step
96 sequences, such as ‘pour-poke-clink’) and ‘part-action’ sequences (which spanned the
97 boundaries of two actions, such as ‘poke-clink-peek’). Adults accurately discriminated action
98 from part-action sequences, which could only be based on the transitional probabilities within
99 these 3-step sequences (Baldwin et al., 2008). Infants from seven months of age demonstrate
100 similar segmentation skills for familiar action sequences such as cleaning a kitchen (Baldwin,
101 Baird, & Saylor, 2001), and for novel, abstract movement sequences (Stahl et al., 2014).

102 Building upon these studies, which measured sensitivity to action structure post-
103 observation, Ahlheim and colleagues (2014) examined neural responses to statistical structure
104 during observation of action sequences. Results showed that increases in neural activation
105 corresponded to the probability of the occurrence of the next action step in the sequence. These
106 findings confirm that adults can exploit statistical structure while processing continuous human
107 action. They also suggest that observers use statistical learning skills to inform their predictions
108 of upcoming action steps.

109 The current study tested the hypothesis that new action knowledge, acquired via
110 observation, can be ‘fed’ into the motor system and result in a motor prediction of an observed
111 action based on visual statistical learning. Infants, who have a limited knowledge base for many
112 of the actions they observe—in terms of observational and motoric experience—present an ideal
113 opportunity for investigating this question. A developmental approach allowed us to directly test
114 the effect of introducing naïve participants to novel perceptual information about action
115 sequences, and whether this new knowledge is used to generate predictions in their motor

system. In a previous study, we showed that 18-month-old infants can learn statistical regularities in continuous action sequences and predict upcoming actions (Monroy et al., 2017). Importantly, infants correctly anticipated more frequently when they observed sequences performed by a human actor, relative to infants who observed a non-action event sequence. This finding supports the hypothesis that the motor system is involved in the perception and prediction of observed actions. Building upon this prior work, we conducted a combined training and EEG study with 18-month-old infants. Infants were first trained over three days by observing videos of action sequences in which one action pair was deterministic: the second action always followed the first action of this pair and was thus 100% predictable. The remaining actions in the sequence were random and thus less predictable. Following this training phase, infants participated in an EEG test session in which they observed a novel sequence featuring the same statistical structure as the training phase.

A decrease in power of the mu rhythm overlaying motor regions is an established index of anticipatory activation occurring prior to the onset of an observed action in infants and adults (Marshall & Meltzoff, 2011; Southgate, Johnson, Osborne, & Csibra, 2009). The mu rhythm, also sometimes referred to as sensorimotor alpha, features reduced power during both action execution and observation (Fox et al., 2016; Vanderwert et al., 2012). In infants, this suppression is also observed prior to the onset of an observed action, suggesting that the mu rhythm reflects predictive activity in the human mirror neuron system (Southgate et al., 2009). We hypothesized that the mu rhythm would be suppressed over the motor cortex, reflecting an increase in motor activity, in anticipation of upcoming actions infants could predict based on statistical regularities learned through observation. Conversely, we hypothesized that infants would show no such anticipatory activity for actions which occurred at random and that they could thus not predict.

2.0 Method

2.1 Participants

Twenty-eight infants ([mean age = 18.55 months, \$SD = .41\$, 17 males](#)) were included in the final sample. Our predetermined target sample size of approximately 25 infants was based on conventional standards for studies that measure the mu rhythm in infants (Gerson et al., 2015; Marshall, et al., 2011; Southgate et al., 2009). Sixteen infants were tested but excluded from the final analysis due to refusal to wear the EEG cap ($n = 4$), insufficient artifact-free trials given a minimum requirement of 3 trials per condition ($n = 9$), [not completing the required 3 days of home training](#) ($n = 1$), or experimenter error ($n = 2$). This attrition rate is not atypical in infant EEG studies (Stets et al., 2012). All parents gave written consent, and families received a small gift or 20 euros for participation. Participants were recruited from a database of interested families from the surrounding region of Nijmegen, a middle-sized city in the Netherlands. All procedures were approved by the local ethics committee.

2.2 Stimuli and Materials

Three training videos and one test video were created, which were identical in length (7m) and statistical structure. Videos featured an adult performing an action sequence on a box-shaped toy which afforded six unique object-directed actions (Fig. 1). Action sequences consisted of deterministic and random action pairs, which were presented with a brief fixation cross between each pair. Deterministic pairs consisted of two pre-selected actions occurring in the same order, such as ‘slide’ always followed by ‘bend’, and repeated 10 times throughout the sequence. Random pairs were comprised of any other combination of the six objects on the toy. The order of all pairs was shuffled pseudo-randomly in each of the four videos. [Thus, infants observed a novel video on each training day and during the test phase.](#) Three sets of stimulus

videos were created, in which the two actions comprising the deterministic pair were uniquely selected from the six possible actions. These three video conditions were counterbalanced across infants.

Fig. 1 illustrates the presentation of an action pair. There were 60 total pairs in each video featuring 10 deterministic pairs and 50 random pairs for a total of 120 observed actions. Thus, during the learning phase, infants were presented with a maximum of 360 total actions and 30 repetitions of the deterministic pairs over the three days. All actions were presented an identical number of times (i.e. 20) to ensure that infants received equal exposure to all six actions.

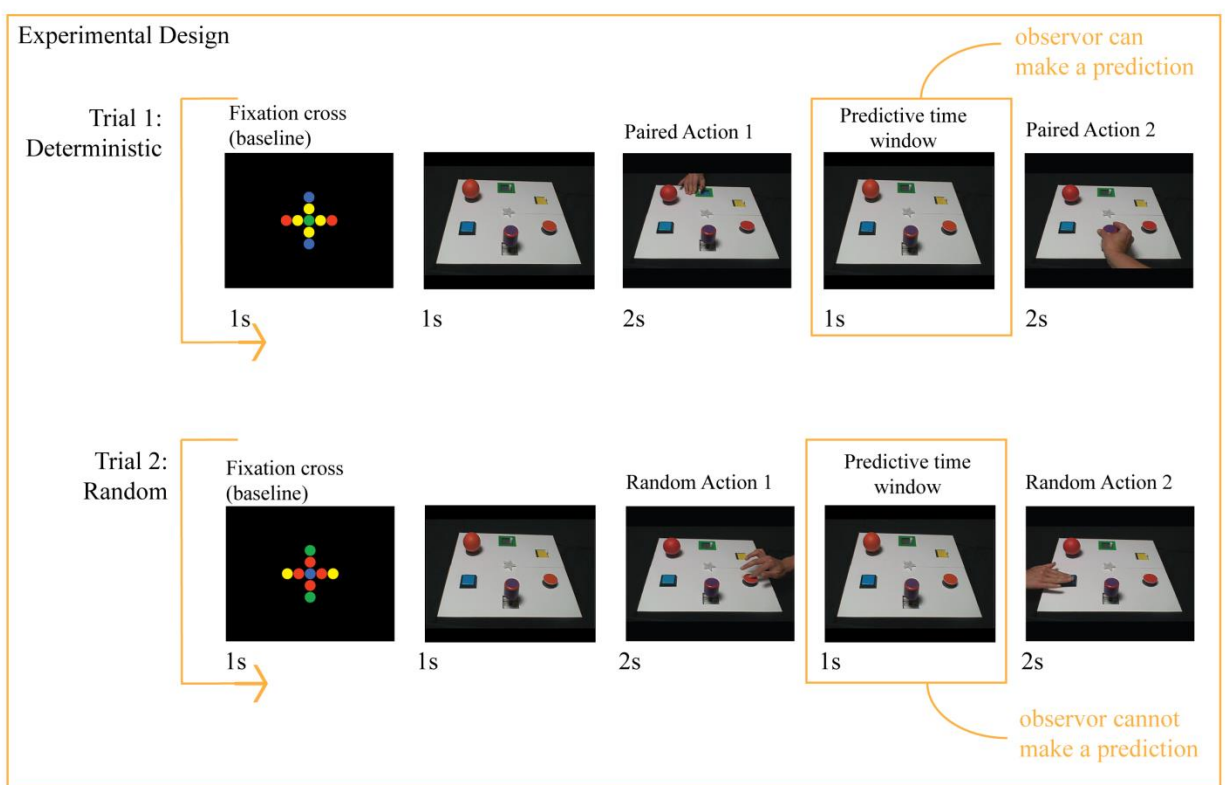


Figure 1. (A) Example frames from video stimuli illustrating two successive trials. Trials began with a static fixation cross, followed by four successive clips played continuously (7s total). EEG markers were time-locked to the onset of each clip. Yellow boxes indicate the two condition time windows used for comparison in the EEG analysis: both conditions are perceptually identical (a

1s still frame with no action occurring), but in the Deterministic condition, infants can make a prediction about the subsequent action based on statistical likelihood, whereas in the Random condition they cannot make a prediction better than chance. The fixation cross was used as a baseline condition in the analyses.

Videos were divided into four blocks, with the orientation of the toy relative to the camera rotated in each block. This ensured that infants could not simply learn the physical location on the screen where each action occurred, as the objects' spatial locations were dissociated from their temporal position in the action sequence. In addition, we imposed the following constraints: all actions occurred with equal frequency (20 times); no pair could occur more than two times consecutively, random pairs could not consist of the same action twice, and deterministic pairs were evenly distributed among the four blocks of the videos. Lastly, no sound was played during any of the videos.

2.3 Procedure

2.3.1 Training phase.

Parents were asked to show each of the three learning videos to their infants at home once per day over the three days immediately prior to their lab appointment. These videos were made available to parents via links on YouTube (www.youtube.com) which were sent to them by email (video links are provided in the Supplementary materials). We instructed parents to play the videos to their infants in a quiet setting with minimal distraction and to maintain identical viewing conditions each day if possible. They were further instructed to watch the videos with their infant seated on their lap approximately one meter from the viewing screen, to mimic the conditions in the laboratory they would experience during the EEG session.

Parents were asked to fill out a detailed diary at home containing information about each video session, including the number of minutes the child watched the movie and their own rating of their infant's average attention to the screen on a scale from 1 to 5. In addition, they were asked to record the type of device they used to watch the videos (e.g., laptop, television screen, or tablet), the time of day, and any additional notes about each training day. The aim of the diary was to assess whether parents complied with the instructions and to measure potential individual differences in infants' exposure to the training videos. All parents but one brought completed diaries with them to the EEG lab session. The mean number of minutes that infants watched the three training videos at home was 13.06 minutes ($SD = 5.9$; $range = 1-21$), which yielded an average of 18.44 observations of the Deterministic pair. Mean rating of attention on the five-point scale was 3.07 ($SD = 1.21$, median = 3.33). [Additional data and analyses from the training phase can be found in the Supplementary materials \(S1 and S2\).](#)

2.3.2 EEG session (test phase).

Test sessions took place on the day following the final training day and consisted of an action observation phase followed by an action execution phase. Infants were first familiarized with the environment while the procedure was explained to the parent. Experimenters then fitted an infant-sized EEG cap to the infant (ActiCap, Brain Products, Munich, Germany) with 32 active electrodes arranged according to the standard 10-20 configuration. Following capping, EEG was recorded continuously while infants sat on a caretaker's lap in a shielded testing room. The EEG signal was referenced online to FCz and re-referenced offline to the average of all electrodes after excluding noisy channels. The mean number of channels included in the average reference was 22 ($SD = 3$). During measurement, the signal was amplified using a Brain-Amp amplifier, band-pass filtered (0.1–125 Hz) and digitized at 500Hz.

Infants were next shown the test video displayed on a monitor at approximately 50cm distance from the infant and caretaker. An experimenter monitored a live video feed of infants' behavior from an adjacent room and initiated attention-grabbers (brief, salient cartoons) whenever necessary to regain the infant's attention. Trials containing or following attention-grabbers were excluded from further analyses. After all trials were completed or when infants lost interest, an action execution phase began. The purpose of this phase was to identify the sample-specific mu frequency range, as defined by a decrease in power during overt movement relative to baseline (Meyer et al., 2016). The experimenter turned off the video monitor and placed the toy stimulus in front of the infant. Infants were allowed to play with the toy for several minutes or until they began to lose interest. The entire testing session was video-recorded for offline movement and behavior analysis.

2.4 Data Analysis.

2.4.1 Coding for movement artifacts and visual attention.

Video recordings of the action observation phase were coded offline frame-by-frame for infant movement. Trials that contained any whole body (e.g., kicking) or single-limb (e.g., moving one arm) movement were marked as invalid and removed from analyses to eliminate motor activity related to overt motor movements during action observation. Trials in which the infant was not looking at the screen were marked as invalid and removed from analyses as well. Across infants, 32.41% of all trials were removed from analyses based on these criteria. These coding procedures are commonly used for infant EEG studies (Hoehl & Wahl, 2012).

2.4.2 Identification of the mu rhythm.

To investigate differences in motor activity during anticipation of deterministic and random actions, we first identified the mu rhythm in the current sample of 18-month-old infants.

Video recordings from the action execution phase were coded offline and epochs were selected in which the infant reached for or manipulated one of the objects on the toy. These epochs were segmented into 1s trials for data processing (see *EEG processing*). To verify that the frequency range in our sample was within the expected range for this age (Marshall et al., 2002), the mean power spectrum was inspected in the 2–50Hz range during baseline and action execution conditions across central channels (C3, Cz and C4; Fig. 1). Consistent with the literature (e.g., Marshall et al., 2011; Nyström et al., 2011), data inspection indicated a clear alpha peak around 8 Hz (± 1 Hz) in which power during action execution was lower compared to baseline, despite broadband differences. Consequently, a sample-specific frequency range of 7-9Hz was used to compare our conditions of interest in the action observation phase.

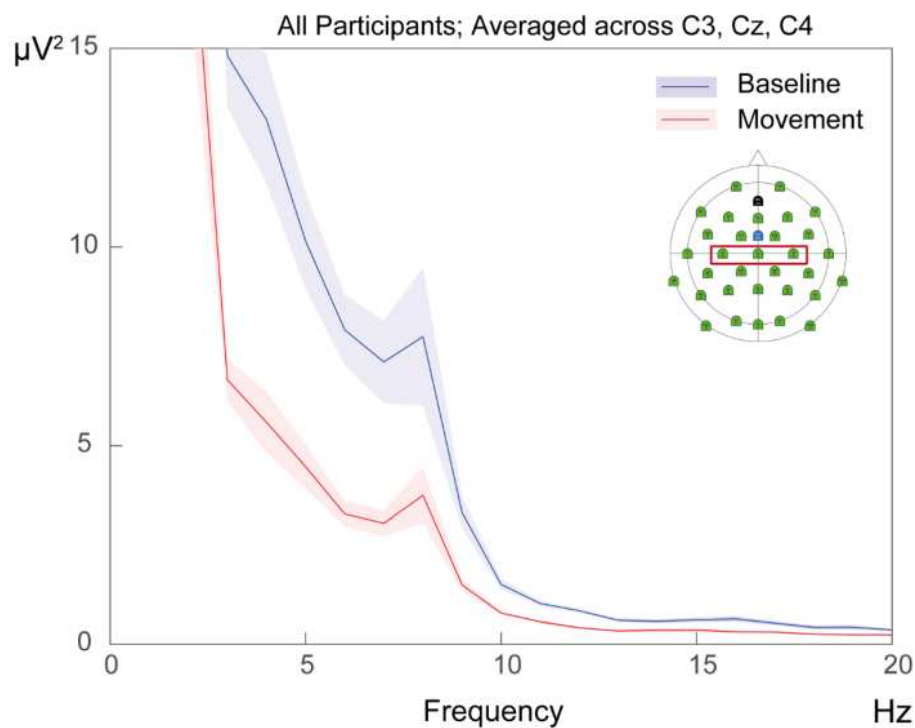


Figure 2. (A) Power values as a function of frequency (Hz) for the action execution and baseline trials. The mu rhythm is clearly visible as a sharp peak between 7 and 9Hz. Electrode

layout depicted on the right; selected channels corresponding to motor regions are outlined in red. Shaded areas represent the standard error of the mean.

2.4.3 EEG processing.

Data were analyzed using Fieldtrip, an open source toolbox for Matlab (Oostenveld et al., 2011). Each action pair was divided into two trials: the 1-second fixation cross (Baseline condition) and the 1-second time window of still-frame preceding the second action, which became the Deterministic and Random conditions depending on the pair (Fig. 1). Trials were detrended, corrected by the mean of the entire segment, and a DFT filter was applied to remove line noise. They were then visually inspected for artifacts such as noisy channels or muscle artifacts (Marshall et al., 2011; Meyer et al., 2016). Segments in which infants were not attending to the screen based on video recordings of the session were rejected. Based on prior work, participants were required to have at least three artifact-free trials per experimental condition (to be included in further analyses (Kaduk et al., 2016; Monroy et al., 2017). Table 1 contains the mean number of trials included in the analysis for each condition after artifact rejection.

Table 1.

Mean number of artifact-free trials during the test phase (SD).

<u>Baseline Condition</u> (max = 60)	<u>Deterministic Condition</u> (max = 10)	<u>Random Condition</u> (max = 50)	<u>Action Execution phase</u>
<u>17.64 (11.08)</u> <u>Range: 3-52</u>	<u>4.54 (1.75)</u> <u>Range: 3-8</u>	<u>16.39 (10.25)</u> <u>Range: 4-41</u>	<u>12.93 (11.39)</u> <u>Range: 3-45</u>

Following artifact rejection, we performed a fast Fourier transform using a multitaper method (Hanning taper) to estimate power values between 7-9Hz (see *Identification of the Mu Rhythm*). Based on visual inspection of the data (Fig. 2), we also analyzed the mean log-

transformed in the theta rhythm (3–6Hz). Results from this post-hoc analysis are described in the Supplementary file (S3).

3.0 Results

We first conducted a repeated-measures ANOVA with mean normalized power of the mu rhythm over central sites (C3, Cz, and C4) as the dependent variable and Condition (Deterministic, Random, Baseline) as a within-subjects factor. This revealed a main effect of Condition, $F(2.54) = 5.22$, $p < .01$, $\eta_p^2 = .16$ (Fig. 3). A one-sample Kolmogorov-Smirnov test revealed the Random condition in the occipital region, $p = .03$, differed significantly from a normal distribution. No other dependent measures differed from a normal distribution, $ps > .20$. There was one outlier (+/- 3SD from the mean) in the Baseline condition over central channels; however, as results did not change when this participant was excluded, we included all participants in our analyses.

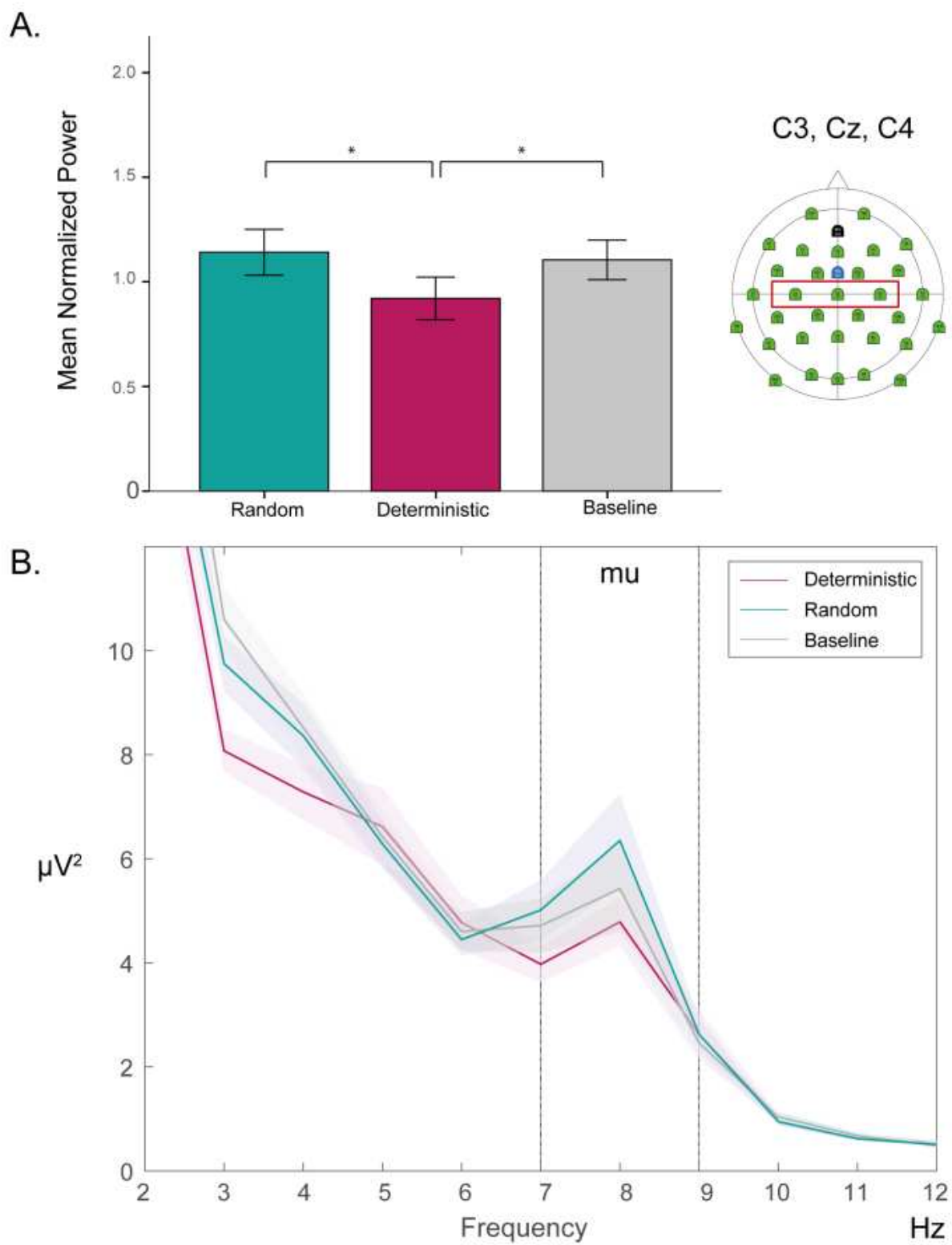


Figure 3. (A) Mean log-transformed power depicted for the two experimental conditions (Deterministic, Random) and the baseline condition (a fixation cross) over central channels overlaying motor regions (electrode layout depicted on the right; selected channels are outlined in red). Error bars represent the standard error of the mean. (B) Power values as a function of frequency (Hz). Shaded areas represent the standard error of the mean. Gray dotted lines indicate the selected mu frequency range (7–9 Hz).

Pairwise comparisons confirmed that power in the mu rhythm over central channels was lower in the Deterministic condition relative to both the Random and Baseline conditions (p s < .02; see Table 2). There was no significant difference between the Random and Baseline conditions ($p = .56$). These findings show that motor activity selectively increased in anticipation of the deterministic actions and not prior to random actions.

Table 2.

Paired t-test comparisons of mean normalized power for the mu rhythm (7-9Hz) over central channels ($N = 28$).

Paired sample t-tests	Mean Difference (<i>SD</i>)	<i>t</i> (27)	p-value	95% CI
Random - Deterministic	.22 (.44)	2.64	0.01	[0.05, 0.39]
Baseline - Random	-.04 (.32)	-0.59	0.56	[-0.16, 0.09]
Baseline - Deterministic	.18 (.39)	2.51	0.02	[0.03, 0.34]

Based on previous literature (Vanderwert et al., 2012), we expected mu suppression to reflect activation of the motor cortex and thus be specific to channels over motor regions. To investigate the topographical specificity of the observed mu suppression, we also examined activity in the 7-9Hz range over occipital channels (O1, Oz, and O2) located over the visual

311 cortex. We did not expect visual activity to differ between Deterministic and Random conditions
312 because the input was perceptually identical. A repeated-measures ANOVA with mean
313 normalized power as the dependent variable and Condition (Deterministic, Random, Baseline) as
314 a within-subjects factor yielded a main effect of Condition, $F(1,43) = 6.34, p < .01, \eta_p^2 = .19$
315 (Fig. 4). [Time-resolved power plots for central and occipital regions are depicted in the](#)
316 [Supplementary file \(S4\).](#)

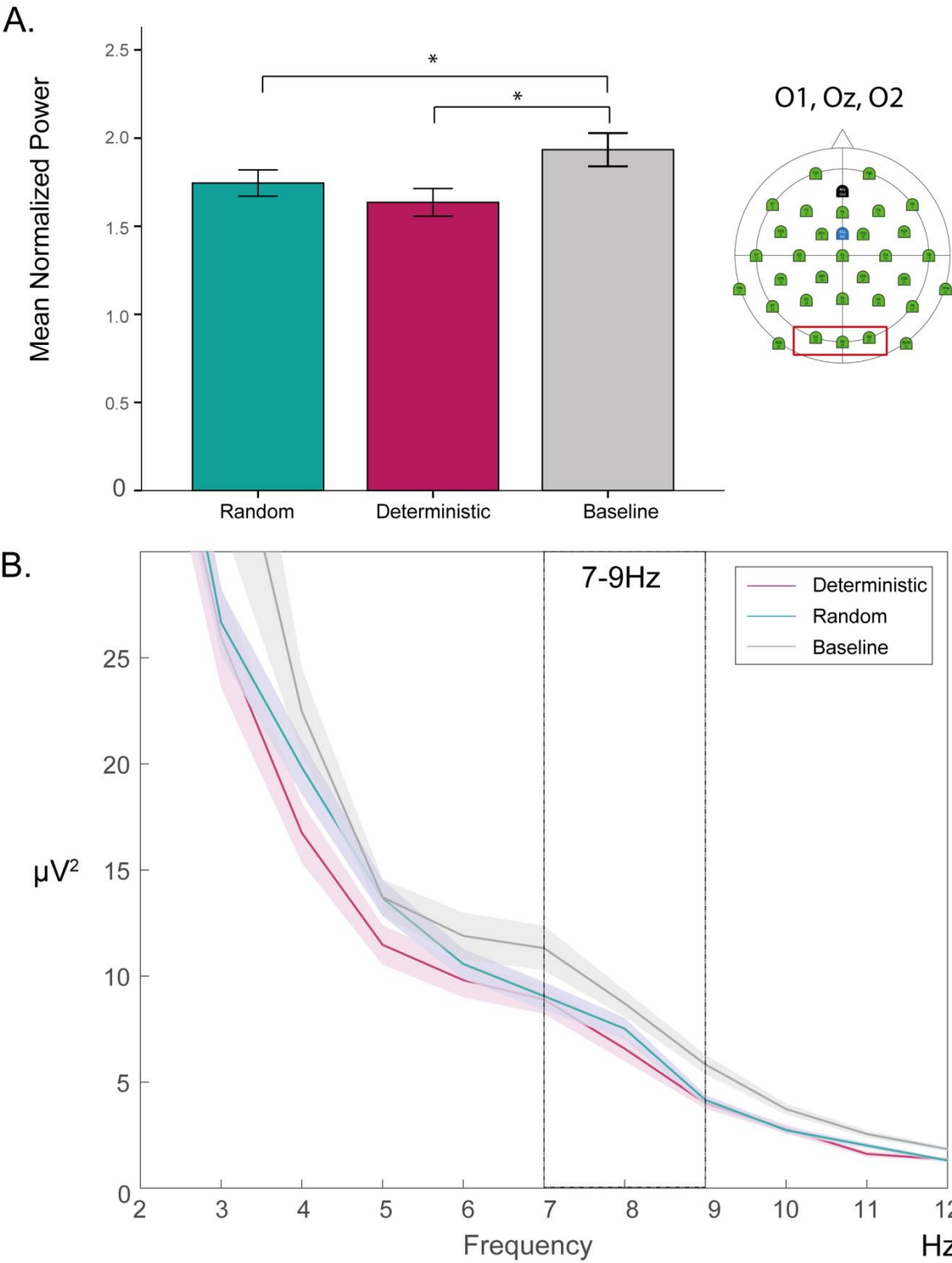


Figure 4. (A) Mean log-transformed power depicted for the two experimental conditions (Deterministic, Random) and the baseline condition (a fixation cross) over occipital channels corresponding to visual regions (electrode layout depicted on the right; selected channels outlined in red). Error bars represent the standard error of the mean. (B) Power values as a function of frequency (Hz). Shaded areas represent the standard error of the mean. Gray dotted lines indicate the selected mu frequency range (7–9 Hz).

Pairwise comparisons revealed that normalized power during Deterministic and Random conditions was lower than during the Baseline condition (mean difference_{Deterministic-Baseline} = -.30, $t(27) = 4.34$, $p < .001$, mean difference_{Random-Baseline} = -.20, $t(27) = 2.62$, $p = .01$, respectively). There was no significant difference in normalized power between Deterministic and Random conditions (mean difference_{Deterministic-Random} = -.11, $t(27) = 1.78$, $p = .09$). Thus, power reduction reflecting visual processing was greater during predictive time windows (displaying the toy stimulus) than during the baseline (displaying the fixation cross), regardless of the upcoming action's probability. These results confirm that the differential mu suppression during anticipation of deterministic relative to random actions was specifically observed over motor, and not visual, regions.

4.0 Discussion

The current study is the first to examine whether new knowledge learned through observation in infancy can be 'fed' into the motor system and thereby used for predicting upcoming actions. Until now, research on action perception has focused on the role of statistical learning in action segmentation and prediction, or on the role of the motor system in generating action predictions. Using a developmental approach, we investigated how these two systems

341 interact by examining whether infants make motor predictions about upcoming actions based
342 solely on visual statistical learning. In line with our hypothesis, findings revealed suppression of
343 the infant mu rhythm, an index of motor activity, during anticipation of upcoming actions that
344 were statistically deterministic, and not for random actions. Infants were not simply anticipating
345 that any action would occur; rather, the observed motor activated reflected anticipation of
346 specific actions based on their statistical likelihood. Moreover, as the videos used in the EEG
347 session had never been seen before, infants could only base their predictions on previously
348 learned transitional probabilities within action pairs. These findings provide the first evidence for
349 motor-based predictions based on information acquired through visual statistical learning.

350 Our findings are in line with recent frameworks which propose that prior action
351 knowledge is fed into generative models in the motor system (Kilner, 2011; Schubotz, 2007). In
352 the current study, infants learned the transitional probabilities between sequential actions from
353 observation alone. The motor system was then able to access this new knowledge and infer the
354 most likely upcoming action. In addition, the current study extends this framework from
355 predicting single action events (e.g., Kilner, et al., 2004) to predicting sequential action steps.

356 These results are also consistent with prior evidence for statistical learning as a
357 foundational mechanism underlying infants' developing understanding of their sensory
358 environment (for a review, see Krogh et al., 2013). Statistical learning is likely a core mechanism
359 that accounts for the human ability to build expectations about upcoming sensory events.
360 Statistical learning abilities may thus also be an important pathway through which infants
361 develop conceptual knowledge about observed actions (Ruffman et al., 2012). In the current
362 study, infants were not simply learning raw frequencies of occurrences, as each action was
363 presented an equal number of times. Rather, infants could only rely on the transitional

[probabilities between action events to form predictions, which is consistent with prior research on infant SL abilities](#) (Stahl et al., 2014). [Future research could target the specific aspects of the structure that infants were able to encode, such as joint or conditional probabilities.](#)

A separate line of evidence has shown that infants' own actions are another important source of information linked to action processing (Hunnius & Bekkering, 2014). Infants can acquire new sensorimotor associations between self-produced actions and the same actions when they observe them performed by others (Gerson et al., 2015; Paulus et al., 2012). However, until now these two sources of information—active and observational experiences—have been considered complementary but separate from one another (e.g., Calvo-Merino et al., 2006). The current findings challenge this notion by providing evidence that the motor system can predict actions from observational experiences alone, suggesting that these two pathways are rather part of one integrated mechanism.

In line with this notion, neuroimaging research in adults reveals that brain regions relevant for statistical learning also overlap with regions of the action-observation network (Ahlheim et al., 2014; Turk-Browne et al., 2008). [According to Kilner \(2009\) the action-observation network relies on reciprocal connections with domain-general regions to generate predictions. These regions are likely to include those involved in visual statistical learning, such as the medial temporal lobe and the hippocampus, which are activated when statistical regularities provide predictive cues of upcoming stimuli](#) (Turk-Browne et al., 2008, 2010).

[An alternative interpretation of our data could be that the observed power reduction in the 7-9Hz range reflects a more general suppression of the alpha rhythm, rather than the sensorimotor mu rhythm. As the two rhythms share an overlapping frequency band, it is possible that our findings reflect modulation of the 'classical' alpha rhythm which is thought to reflect](#)

387 general processing of visual stimuli (Bazanov & Vernon, 2014). The observed reduction in
388 alpha power prior to the predictable action might then reflect enhanced visual attention in
389 anticipation of a stimulus that is expected relative to one that is unknown, although if so this
390 should have been observed primarily in the occipital channels. However, our methodology was
391 designed to reliably separate the mu rhythm from the alpha rhythm as suggested in the literature
392 (Bowman et al., 2017; Fox et al., 2016). First, we included both action execution and observation
393 phases, which is crucial to identify the mu rhythm as it is characterized by a suppression over
394 motor regions during movement relevant to non-movement (Cuevas et al., 2014). Second, we
395 report findings from multiple electrode sites, including visual areas, which did not show the same
396 pattern of results. Third, we controlled for visual confounds by analyzing the predictive time
397 window prior to the actions themselves during which the stimuli were visually identical. Thus,
398 the observed activity was most likely related to the infants' anticipation of the forthcoming
399 stimulus rather than ongoing visual processing

400 Due to the limited number of trials included in our experimental conditions, findings
401 from the current study should be interpreted with caution and replicated in future work. Still, our
402 main findings regarding the mu rhythm are consistent with prior research in terms of both its
403 functional significance during action anticipation (e.g., Southgate et al., 2009) as well as the
404 location and frequency range in infants (Marshall et al., 2002; 2011, Nyström et al., 2011). In
405 addition, the current study is limited to the interpretation of neural data. Given the challenges of
406 simultaneous EEG and eye-tracking recordings in infants, we did not collect eye-tracking data,
407 which would have allowed us to examine anticipatory eye movements as an additional measure
408 of learning and prediction. Directly relating the current findings with behavioral findings from

prior research (e.g., Monroy et al., 2017) using simultaneous recordings—for instance, with adults—would be an interesting avenue for future research.

4.1 Conclusion

In conclusion, we show that prediction of an upcoming action based on its statistical likelihood elicits activation of the infant motor system. These results extend the functional role of infants' statistical learning to the development of the human action-observation network. Infants can acquire new knowledge of an upcoming action by using their powerful statistical learning abilities, and subsequently use this knowledge to generate action predictions in their motor system.

Acknowledgments.

We would like to thank Lorijn Zaadnoordijk, Ricarda Braukmann, Angela Khadar and Birgit Knudsen for their generous help with recruitment and data collection. We would especially like to thank Pascal de Water for invaluable help with programming the experiment.

Funding: This project was funded by an Initial Training Network (ITN) of the People Marie Curie Actions grant—Seventh Research Programme (FP7) of the European Union (FP7ITN2011-289404).

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